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Chinese household food waste and its' climatic burden driven by urbanization: A Bayesian Belief Network modelling for reduction possibilities in the context of global efforts

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ABSTRACT

Consumer food waste usually exceeds food losses when a developing country transitions to a developed one. With this notion, China, which is experiencing socioeconomic transition, is projected to be a future hotspot of global food waste. However, the mechanism of food waste generation is more complex than that of food losses, because various driving factors entangle with each other in a non-linear way. Here, by linking household survey data and reviewed life-cycle-assessment dataset, we quantified food waste in Chinese typical provinces, and developed a Bayesian Belief Network (BBN) model to reveal the mechanism of household food waste generations. We explored the possibilities of food waste reduction based on the Chinese contextualized scenario analysis, and further revealed the association of food waste and food security at global scale. Results show that the average food waste varies among Chinese provinces ranging from 12 to 33 kg cap^{-1} yr^{-1}, with carbon footprint from 30 to 96 kg CO_2e cap^{-1} yr^{-1}. Animal-derived food accounts for 5–18% in weight, but disproportionately for 18–40% of carbon footprint. The accuracy of BBN model is 78%. Sensitivity analysis shows that refrigerator ownership ranks first in determining food waste generations, compared to other factors of income, education, household size, and urbanization levels; and ages of family members. At the global scale, household food waste climbs sharply when food-security status of a certain country rises. China with its barely satisfied food-security status would astonish the world if we followed the global waste trajectory due to its largest population. However, according to our BBN-based scenarios, it is too early to say that China will become a global hotspot of food waste considering its specific socioeconomic and cultural backgrounds in its rapid urbanization period.

1. Introduction

Increase in food supply is being observed in many parts of the world as a result of technological innovations being adopted to feed the growing population. For example, China astonished the world by feeding 21% of the global population with only 6% of the world's water resources and 9% of arable land, but at a great environmental cost (Piao et al., 2010). Driven by rising wealth, dietary changes and urbanization, China's future food demand is projected to increase by at least 40% in 2030 (Zhang et al., 2011), or double in 2050 compared to 2009 (Hamshere et al., 2014). However, increasing food supply is limited by water and farmland availability (Wei et al., 2015), especially in the context of climate change (Piao et al., 2010). Thus, alternative strategies that promote sustainable diets, reduce food losses and waste (FLW) are badly needed (Shafiee-Jood and Cai, 2016). Given its huge population and developing trends, China is projected to become one of the global food-waste hotspot in the near future (Hiç et al., 2016).

Food losses and waste coexist, but their roles vary in different

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wealth contextualized economies. The former occurring within the supply chain is prevalent in developing countries, while the latter is a bigger challenge in most developed nations (Aschemann-Witzel, 2016). As an emerging country, China is experiencing socioeconomic transition characterized by rapid urbanization (Bai et al., 2014), which consequently enriches its city dwellers and complicates the urban food system in a hidden way as Seto and Ramankutty (2016) summarized. Thus, compared with food losses, food waste by Chinese consumers seemingly deserves a priority to be tackled in a long run, referring to the differentiated shares of FLW rates along the whole food supply chains of United States and South Africa (Fig. 9 of Xue et al., 2017).

However, only few studies have estimated China's FLW at the national scale and its environmental impacts. Liu (2013) by reviewing fragmented materials, showed that less efficient storage facilities were the largest contributors to food loss over years, but consumer waste has begun to balloon currently. Meanwhile, Liu et al. (2016) using the loss factors method estimated that 19% of the grains were lost or discarded, implying that 135 billion m^3 of WF and 26 million ha of farmland were used in vain, with consumers identified as a single largest cause. By using survey data, Song et al. (2015) showed that an annual 21 Mt of food was discarded from the Chinese households, equivalent to 54 $MtCO_2e$ of carbon emissions, 24 Gm^3 of water resources and 23 Mgha of land occupations. Hiç et al. (2016) using "food surplus" quantified the consumer food waste at global scale, and pointed out that China's food waste was responsible for 110 $MtCO_2e$ of carbon footprint in 2010 and this rising trend of food waste would continue in the future.

Raising environmental awareness on FLW is critical for the public, but it is not enough unless reduction strategies are implemented. Thus, understanding the causes of household food waste is a first step for further reductive actions, on which extensive studies are available especially in developed countries. For example, Aschemann-Witzel et al. (2015) reviewed literature and showed income, household size, resident age, education level, storage behavior, as well as societal trends of urbanization etc., were key factors that contributed to the generations of household food waste. In-depth review by Shafiee-Jood and Cai (2016) further revealed that avoiding food waste was more complex than reducing food losses because the underpinning socioeconomic factors do not act in isolation, but rather in a coupled and non-linear format. This is the reason why Seto and Ramankutty (2016) came up with a recommendation to disentangle income from the urbanization effect when food losses and waste are concerned. Experiences from France and USA (Mourad, 2016) and the latest review (Hebrok and Boks, 2017) highlighted that macro-socioeconomic factors that affect the hierarchical solutions to reduce food waste were urgently needed from an intervention perspective.

In China, although factors causing household food waste have been identified together with the environmental benefits of waste reduction, no study is available that investigates reduction actions. One of the primary challenges of the current statistical methods, such as regression analysis (Koivupuro et al., 2012), cluster analysis (Mallinson et al., 2016), confirmatory factor analysis (Stancu et al., 2016), and proportional odds models (Setti et al., 2016), is their inability for conceptual reasoning about the uncertainties of waste drivers. Moreover, these models are not capable of handling the nonlinear causal-effect relationships from a system perspective. Thus, integrated modelling approaches like the Bayesian Belief Networks (BBN) (Laniak et al., 2013) that provide insight into the holistic interactions between food waste and its driving factors, are needed to aid scientific strategies for reducing future waste (Aschemann-Witzel et al., 2015). Besides, Chinese diets differ considerably from northern to southern provinces due to the wide geographical distance. This situation is viewed to generate a varied pattern of food waste because: as a specific food is more consumed, the more it is usually discarded (Song et al., 2015). However, few studies has focused on this variation of Chinese household food waste.

Although BBNs have been used successfully to understand complex systems under various environment domains (Aguilera et al., 2011; Kelly et al., 2013), they have been used to understand household waste generation and reduction possibilities. Here, for the first time, this study aims at: (1) quantifying household food waste and its carbon footprint in typical far-distant provinces in China; (2) innovatively developing a BBN model as an integrated approach to identify key demographic factors that contribute to household food waste reduction; (3) predicting the possibilities of waste reductions by scenarios analysis that is contextualized by Chinese socioeconomic transitioning trends; and (4) summarizing the trajectory of household food waste at the global scale to compare global-trajectory based on China's food waste and BBN-model based results. This study is organized in four sections which include the introduction, materials and methods, Results and discussion, and conclusion.

2. Material and methods

2.1. Household survey

According to the definition of FLW (Parfitt et al., 2010), we regarded the total discards from kitchen and table as household waste, without differentiating the avoidable, possibly avoidable and unavoidable components. This study cited data of food waste from China Health and Nutrition Survey (CHNS), which is the only large-scale longitudinal household-based survey conducted in China. Seven CHNS rounds (i.e., 1991, 1993, 1997, 2000, 2004, 2006 and 2009) in nine provinces were selected for food waste estimates. CHNS uses the income-stratified multistage cluster sampling method, with detailed information summarized by Popkin et al. (2010). A total of 7091 households and 31,161 individuals were included in this study.

For each sampled household, three consecutive days were randomly selected from Monday to Sunday. For each day, all food items of all purchases, home production, processed snack foods and food waste, were weighted and recorded. Besides weighting, food intakes of each individual were written down based on the codes of China Food Composition, and about 1950 types of food were included. At the end of three-days survey, all remaining foods were weighed again and recorded. Food waste was estimated by weight balance when other methods were not possible.

We further extracted demographic information of 5611 households from the last three rounds (i.e., CHNS 2004, 2006 and 2009), and further used in BBN modelling because food codes were unavailable for other rounds. We assigned each household with multiple identifiers if it was surveyed repeatedly in multiple rounds, to avoid possible impacts of demographic changes on food waste. A total of 13,038 'unique' households having sufficient information were compiled to develop the BBN model, on which we revealed the complex mechanism of waste generations by quantifying the possibilities of future food waste reduction.

2.2. Food waste and carbon footprint

We aggregated all 1950 kinds of recorded food into 28 groups (i.e. rice, wheat, maize, tubers and starch, biscuits, bread, sweets, other cereals, dumplings, legumes, beef, lamb, pork, poultry, other meats, eggs, milk, dairy products, yogurt, aquatic products, vegetables, fruits, vegetable oils, dried fruits, beverages, liquor, sugars,

and others). To estimate carbon footprint (CF) reflecting climatic burden, we created a linkage between food waste and a reviewed LCA database of Double Food-Environmental Pyramid model supported by the Barilla Center for Food & Nutrition (BCFN, 2014) because LCA-based food studies are still premature in China. By this method, we quantified Chinese average CF of food consumption to be 1447 MtCO2e yr^{-1} (Song et al., 2015), which is comparable with the parallel estimate of 1308–1618 $MtCO_2e$ yr^{-1} by reviewing China's macro data (Li et al., 2016). Thus, BCFN database is capable of filling current data gaps in China, though it is dominated by European and American food production systems. CF coefficients are available in Song et al. (2017).

2.3. Knowledge review for BBN modelling

Non-linear interactions exist among multi-socioeconomic factors comprehensively influencing household food waste. This situation invalidates current statistical methods (such as regression and cluster analysis). By contrast, BBN that depends on existing knowledge is good at modelling complex system by integrating multiple causal-effect relationships, uncertainties and stakeholder participation (Aguilera et al., 2011; Kelly et al., 2013). Based on its uniqueness, BBN is thus suitable to model household food waste. Following well-established guidelines (Chen and Pollino, 2012), we developed a BBN model to identify key factors influencing household food waste, and quantify the reductions possibilities in the context of China's socioeconomic transitioning trend.

Based on our knowledge on factors influencing household food waste generations (Song et al., 2015), we selected seven key variables (i.e., household income, household size, urbanization level, education level, age of family members), and refrigerator ownership (Heard and Miller, 2016) to develop the BBN model. By using our previous study experience and professional judgment, the cause-effect relationships among all driving factors are listed in Appendix Table A.1. All socioeconomic factors directly influence the generation of household food waste, and these factors interact with each other in a nonlinear way. For example, connections exist between urbanization and education levels, education and income, and average age and average income. Based on previous modelling experiences (Semakula et al., 2016), we organized all the factors into an influence diagram (Chen and Pollino, 2012), as shown in Appendix Fig A.1.

2.4. Model parameterization

We used Netica software, version 5.12 (www.norsys.com/download.html) to perform the BBN model. The structured BBN model consists of three elements: A set of nodes representing variables of socioeconomic factors influencing household food waste; links representing the cause-effect relationships between variables; and a set of probabilities representing the beliefs in a given 'state' of connecting nodes. We discretized the variables of BBN nodes into categorical states (Appendix Table A.2). Each node contains a limited of states (i.e., 2–5) to adequately manage conditional probability tables (CPT), and to obtain accurate projections that capture the corresponding range of input values (Chen and Pollino, 2012).

2.5. Calibration and evaluation

We generated a casefile by organizing data in an Excel sheet of Microsoft. This casefile includes 13,038 observations, and each row represents a household. Then, we randomly divided the casefile into two partitions: A training set ($n = 10{,}430$; 80%) for model development and a testing set ($n = 2608$; 20%) for accuracy evaluation (Fienen and Plant, 2015). Given the link structures (Fig A.1), training dataset was entered into the model as evidence found using parameter-learning method, which determines the CPTs at each node of BBN model (Marcot, 2012).

Based on the average of Chinese food waste (44 g cap^{-1} d^{-1}; Song et al., 2015), we categorized the waste grams of output node into four groups (i.e., <44, 44–100, 100–150 and >150 g cap^{-1} d^{-1}), on which a confusion matrix was generated to evaluate the overall performance of the BBN model. Besides, we used other three indicators of logarithmic loss, quadratic loss, and spherical payoff, to determine how well the BBN model reflect the values compiled in the casefile. We ran the sensitivity analysis to calculate the variance reduction in the food waste node and to identify the key factors contributing to waste generations.

2.6. Predefined scenarios

Macro socioeconomic transitioning contextualizes household food waste. The next several decades will witness three trends in China. First, rapid urbanization will attract between 70% and 75% of Chinese into cities for wealthy life by 2030 and 2050, respectively (Gu et al., 2017). Second, the "Two Child Policy" became law in Jan 1, 2016 (PRC, 2015), overlaying the aging population and will influence the Chinese household size. Third, the "strategy of Invigorating China through Science and Education" since 1995 made more educated people earn higher salaries.

Thus, we generated 21 scenarios for the established BBN model, to reveal the effect of each socioeconomic factor on household food waste generation. For each scenario, we tested the possibilities of food waste generation by changing each state of variables in the BBN model (see Section 3.3).

3. Results and discussion

3.1. Food waste and climate burden

Per capita annual average food waste was calculated for the nine provinces in 1991–2009, as shown in Fig. 1.

Results show that households of Hubei province in central southern China produce most food waste of 29 kg cap^{-1} yr^{-1} on average, while households of Heilongjiang that lies in the extreme northeast China discards the least of 11 kg cap^{-1} yr^{-1}. Provinces of Jiangsu and Guangxi are comparable in household food waste generations of 21 and 19 kg cap^{-1} yr^{-1}, respectively (Fig. 1a). Food waste varies in years. For example, the year 2004 saw the most discard of 39 kg cap^{-1} yr^{-1} in Hubei households, and the year 2009 witnessed that the least waste generation of 8 kg cap^{-1} yr^{-1} by Heilongjiang households (Fig. 1b).

According to the surveys of 2004, 2006 and 2009, we plotted the contribution of each food group to total waste and embedded carbon footprint (Fig. 2). Although food waste varies considerably among provinces, common components are still able to be observed. Plant-derived food sharing 80–93% in weight dominates the waste grams in all provinces, while the animal-derived food accounts for a small portion of 5–18%. Nevertheless, these meager shares of animal-dervided food waste disproportionally contribute to 18–44% of the total carbn footprint generations.

Food waste composition varies among provinces. Rice discards are common in all Chinese southern provinces except Guizhou province (Fig. 2a). For example, households of Guangxi province discard an average of 6 kg of rice annually, equivalent to 40% of the total waste and 36% of all waste associated carbon footprint. By contrast, rice discarded from households of Shandong, Liaoning and Heilongjiang is negligible (less than 0.6 kg cap^{-1} yr^{-1}), because paddy field is limited in these northern provinces.

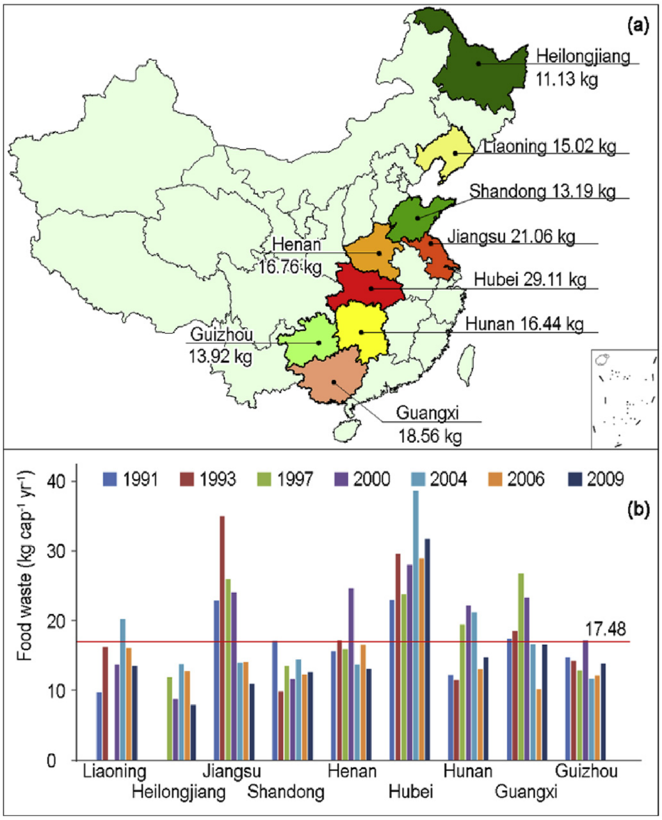

Fig. 1. Household food waste in typical provinces of China according to the seven CHNS rounds. **(a)** Spatial pattern of annual per capita food waste, **(b)** provincial wastage in different years referred to average waste of 17 kg cap^{-1} yr^{-1}.

Heilongjiang households have the most waste of fruits (3.35 kg cap^{-1} yr^{-1}) and least of vegetables (3.93 kg cap^{-1} yr^{-1}). Waste of a specific foodstuff was usually dependent on its consumption. Namely, the more a kind of food is consumed, the more is discarded. If this claim has universal significance, the seemingly contradictory results of wasted vegetables and fruits in Heilongjiang may be explained by the fact: that high fruit waste generation results from the high intake of fruits to balance the insufficient nutrition provisions from the limited vegetable intakes as compared to other provinces. This is because the low mean annual temperature (i.e., negative 4–5 Celsius) in Heilongjiang province hinders local vegetable growth. Lower profits additionally discourage food dealers from importing vegetables by long-distance transport (Wang and Wang, 2010), compared to high-value fruits.

3.2. Model performances

Fig. 3 shows the compiled BBN model for Chinese household food waste, with each bar representing belief or probability. The output node shows a collective effect of all variables on the average waste generations that is expressed by posterior conditional probabilities.

The model has an error rate of 22%, implying an overall accuracy of 78% to predict the possibilities of four levels of household food wastes. The probabilities of households discarding <44 g cap^{-1} d^{-1} is 77.1%, while the probabilities of households to generate waste of 44–100, 100–150 and above 150 g cap^{-1} d^{-1} are 12.6%, 4.6% and 5.7%, respectively. The results of sensitivity, specificity and precision analysis indicate a high performance of the BBN model (Appendix Table A.3). The scoring rule results also confirm the model's strong predictive power with quadratic loss (0.37) scores close to zero, and the logarithmic loss (0.83) and spherical payoff (0.79) approaching 1.

Results of sensitivity analysis are presented in Appendix Table A.4, and the influence of factors on food waste generations is ranked according to the variance reductions. We found that refrigerator ownership was the most significant factor influencing the generations of Chinese household food waste. This result is not surprising, since refrigeration storage have emerged as a popular behavior influencing food waste generations (Heard and Miller, 2016). Household income, education level, household size and urbanization level also show strong influences, and are responsible for a total of 12.4–25.5% of variance reductions. These household factors were reviewed previously (Aschemann-Witzel et al., 2015), but not ranked as done by BBN model from a systematic perspective. Age of family members and provincial regions show the least influence.

3.3. Scenario analysis

In the nonlinear causal-effect BBN model, we tagged each state in each node to 100 to examine its influence on the household food waste node. Fig. 4a–f summarize the waste possibilities of the 21 scenarios.

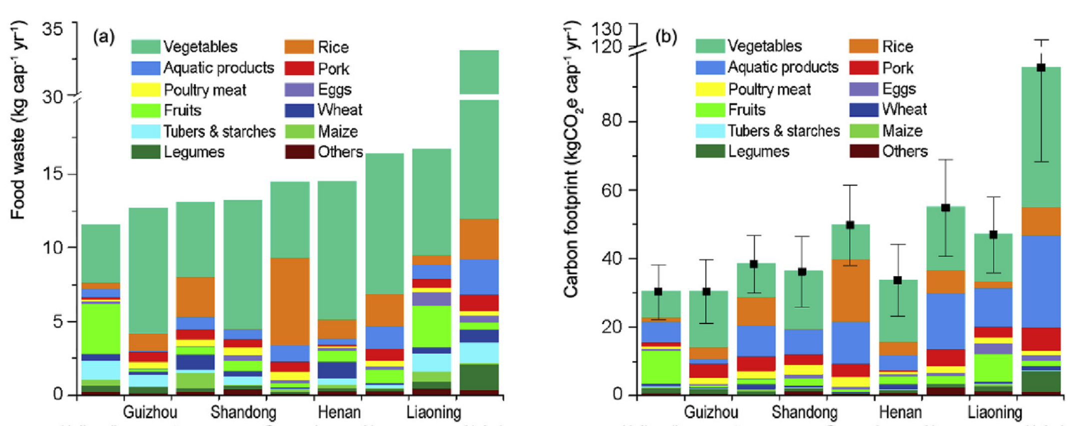

Fig. 2. Climatic burden associated with food waste in Chinese households based on CHNS data of 2004, 2006 and 2009. **(a)** Food waste ranging 12–33 kg cap^{-1} yr^{-1}, and **(b)** carbon footprint averaging 30–96 $kgCO_2e$ cap^{-1} yr^{-1}. Uncertainties of the panel **b** are derived from Monte Carlo simulations.

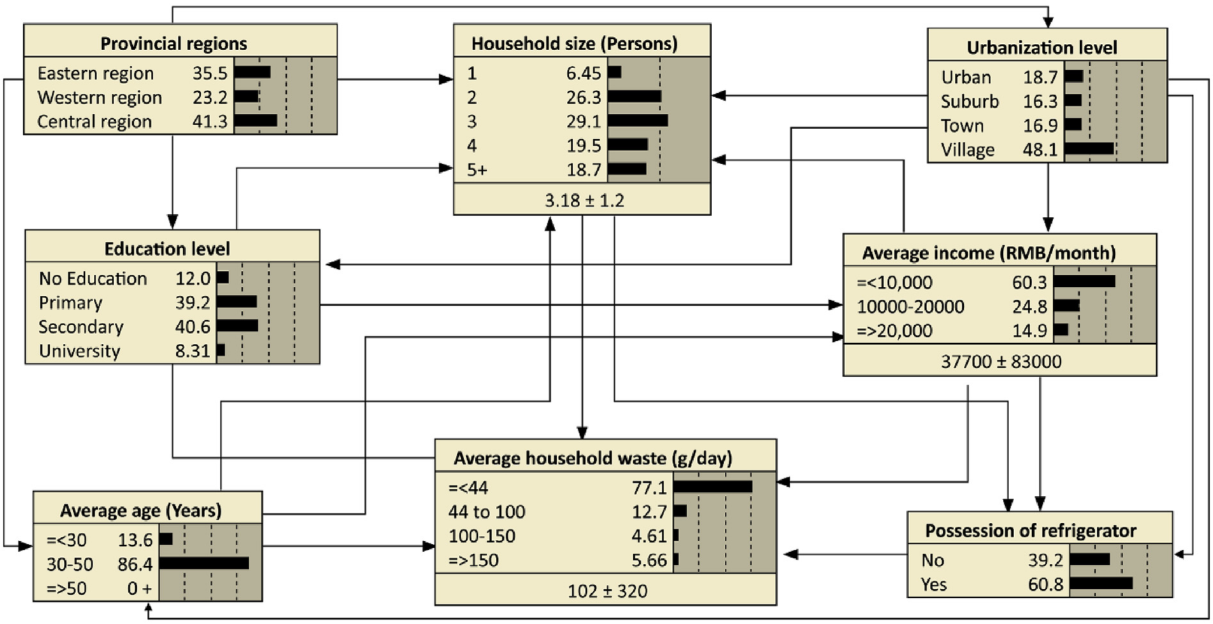

Fig. 3. Bayesian belief network model for per capita average food waste in Chinese households.

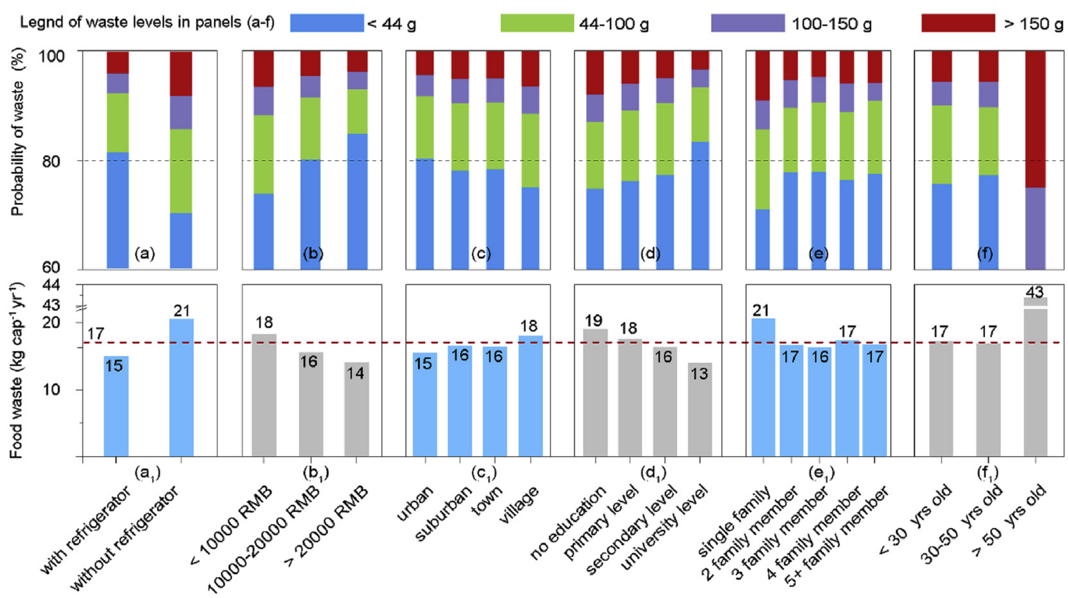

Fig. 4. Possibility of household food waste in the context of China's socioeconomic transitioning scenarios. Impact of **(a)** refrigerator ownership, **(b)** monthly average household income, **(c)** urbanization levels, **(d)** average education level of all family members, **(e)** household size, **(f)** average age of family members on household food waste. The higher possibility of waste in level <44 g cap^{-1} d^{-1} is, the less food is wasted. (a_1)-(f_1) represent projected average food waste corresponding to panels (a)–(f), with reference line as surveyed waste.

Fig. 4a_1-f_1 show that projected kilograms of food waste in predefined scenarios range from 14 to 43 kg cap^{-1} yr^{-1}. Although BBN modelling is capable of quantifying nonlinear effects of household factors on food waste generations, we still go ahead to analyze the role of each factor, and compare the results with previous studies.

3.3.1. Refrigerator ownership

Adopting refrigerator in China can reduce the grams of household food waste. If actions were put in place to increase possession of refrigerators, the likelihood that individuals generate less than 44 g of daily waste would increase to 81.4%; otherwise, reduced refrigerator ownership would generate more food waste (Fig. 4a and a_1). However, there are dissenters to this view. For example, Heard and Miller (2016) revealed the rebound effects of fridge uses on food waste. Besides slowing down food spoils, household freezing storage also leads to higher waste due to consumer's overbuying (Williams et al., 2012), improper storage with higher temperature (Marklinder and Erikkson, 2015) and expired dates (Janssen et al., 2017). Additionally, use of refrigerators may create a necessity to store more cooked food for later convenient consumption during a busy schedule, but leftovers may be thrown away due to their lost tastes (Terpstra et al., 2005).

3.3.2. Household income

If household income improved to more than 20,000 RMB monthly, the probability that households generate less than 44 g cap^{-1} d^{-1} would increase to 84.8%, implying a reduction in food waste (Fig. 4b and b_1). This result attributes to China's high proportion of plant-derived food waste, more than 85% of total in weight. Increased income decreased plant-derived food waste slightly, thus leading to less discards.

However, previous reports gave no clear-cut answers to the role of income in food discards. Household-level studies showed that affluent families with more disposal wealth tended to waste more than these low-income families (Palatnik et al., 2014; Parfitt et al., 2010), and this school of thought was supported by the latest review (Xue et al., 2017), showing that household food waste is positively related with per capita GDP at the global scale. Conflicting options are not scarce. For example, Cox and Downing (2007) showed that households in lower social class discarded more. Melbye et al. (2017) and Williams et al. (2012) found no correlations between household income and waste generations. When considering the detailed typologies of food waste, Setti et al. (2016) even revealed an inverse U-curve in Italia households to reflect the complex relationship of waste and income.

3.3.3. Level of urbanization

The scenario of increased urbanization would make the waste probability of less than 44 g cap^{-1} d^{-1} increase to 80.3%, meaning a slight reduction in food waste generations (Fig. 4c and c_1). This result is consistent with previous study (Song et al., 2015), showing that rural households discard more than their urban counterparts.

Urbanization is not just a single rising of urban population, but covers wider dimensions, such as dietary shift for more animal-products, spatial rearrangement of grocery stores and restaurants, changes of shopping patterns, rising frequency of dine-out, increased food storage, and changed cooking behavior, etc. It should be cautiously aware that the hidden linkages between urbanization and food system is too complicated to be easily disclosed, especially when economic effects are entangled (Seto and Ramankutty, 2016).

3.3.4. Education level

As the average years of family members' education increased, the probability of households to generate less than 44 g cap^{-1} d^{-1} of waste would increase to 83.3% (Figs. 3 and 4d). Compared to the average waste of 19 kg cap^{-1} yr^{-1} for households with no education, the wastage for households with university education decreased to 13 kg cap^{-1} yr^{-1}, although the latter consumes more (Song et al., 2015, Fig. 4d_1). This is attributed to the fact that better educated consumers are more likely than those less educated to know the environmental impact of food waste (Marx-Pienaar and Erasmus, 2014), and choose suboptimal food items from household stocks (Aschemann-Witzel et al., 2017). Sometimes education just affects the waste generations of some specific food categories, such as bakery products as observed by Visschers et al. (2016). Besides, no clear or limited association between education level and household food waste was also reported (Abeliotis et al., 2016; Koivupuro et al., 2012).

In China, its higher education has been growing since 1999. The year 2017 saw about 8 million students graduate from Chinese universities (i.e., ten times higher than that in 1997), or more than two times of current graduates from the US (Stapleton, 2017). Thus, higher education maybe positively reduce Chinese household food waste.

3.3.5. Household size

Decreased Chinese household size to single family would generate more per capita waste, which is reflected by decreased possibilities of food waste less than 44 g cap^{-1} d^{-1} (Fig. 4e and e_1). This result is consistent with our previous report that Chinese single family discards the most (about 20 kg cap^{-1} yr^{-1}) although consuming least (Song et al., 2015). This conclusion that most discards occur in single family was also observed in Italy, Germany, and Finnish households (Jörissen et al., 2015; Koivupuro et al., 2012). Previous studies also showed that large households generated more total food waste (Parizeau et al., 2015), but less average of per capita discard (Parizeau et al., 2015; Quested et al., 2013). When Chinese household size increased, per capita food waste would remain almost unchanged about 17 kg cap^{-1} yr^{-1}.

3.3.6. Age of family members

Fig. 4f and f_1 show that food waste in households of adolescents (<30 years) or wrinkly (30–50 year) are hardly changed, similar to the surveyed of 17 kg cap^{-1} yr^{-1}. As household members advance in their age (>50 years on average), they generate more wastes reaching up to 43 kg cap^{-1} yr^{-1}. However, we are not so convincing to this projection, because it quite differs from currently dominant academic views. These views show that households with older people usually discard less due to the financial and moral considerations (Quested et al., 2013), and specific experience of food scarcity times, such as the World War II (Melbye et al., 2017; Parfitt et al., 2010; Watson and Meah, 2012).

Influences of household size and family age on food waste generations are relative complicated, and may be determined by China's specific cultural context. For example, parents usually live with their children when they are aged, and help to take care of grandsons/daughters. This situation influence food waste in a contradictory way. For one thing, the aged experienced the world's largest famine between 1959 and 1961 (Smil, 1999) cherish grain, and try to reduce food waste; for another, they are likely to provide too much food to express their affection to the next generation. Due to the overlaying of population aging and urbanization (Chen et al., 2017), Chinese household size is hard to project, which lead to significant uncertainties in quantifying household food waste.

3.4. Food waste versus food security

We reviewed household food waste of 28 countries, and calculated the per capita levels according to their population (Table A.5). We plotted the waste level against Global Food Security Index (GFSI, 2012–2016). Then, we projected Chinese household food waste by two approaches: following global waste trajectory (Fig. 5a), and BBN-modeled scenarios (Fig. 5b).

Chinese household food waste is 17 kg cap^{-1} yr^{-1} on average, higher than 7 kg cap^{-1} yr^{-1} in South Africa (Oelofse and Nahman, 2013), but far less than that of 95–115 kg cap^{-1} yr^{-1} in most European countries (FAO, 2011) and 124 kg cap^{-1} yr^{-1} in the United States of America (Buzby and Hymana, 2012). However, the largest Chinese population magnifies the total household food waste up to 21 Mt yr^{-1} (Song et al., 2015) that is slightly less than the wastage of 38 Mt yr^{-1} in USA (Buzby and Hymana, 2012).

Fig. 5a shows that, although the relative low coefficients of R^2 (i.e. 0.34 and 0.39) mean weak projections of food wastes referring to the data points of literature reviewed, positive trends are still capable of being observed. The natural logarithm transformed fitness has stronger projecting ability, with higher R^2, F ratio of variance analysis and the estimated coefficient of slope featured by t statistics (4.27, $p < 0.001$), thus outperforming the linear regression with a constant slope. By comparing the two regressions, we found the global GFSI threshold of 77.85. When food security status of an affluent country reaches the threshold, household food waste

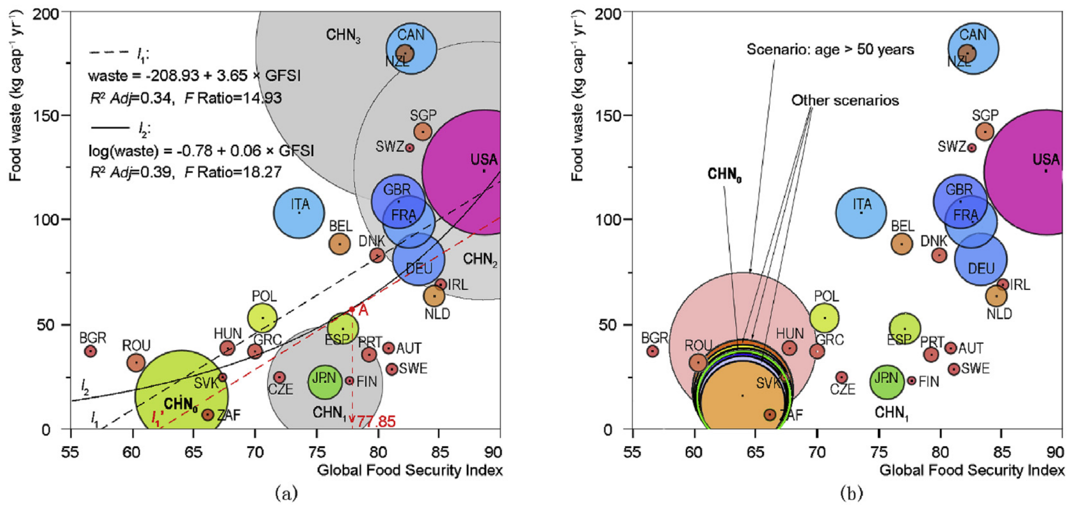

Fig. 5. Projections of Chinese household food waste based on **(a)** global waste trajectory, and **(b)** BBN-based scenarios. Regression of food waste against the average Global Food Security Index during 2012–2016. In panel **a**, lines l_1 and l_2 represent linear regression and natural logarithm transformed regression, respectively. Line l_1' is parallel to l_1 and tangent to l_2 at point A. The height of each bubble center represents per capita food waste, and the bubble size represents the total waste considering population.

begins to climb more rapidly than those in less food-secured nations.

China has an average GFSI of 63.90 in 2012–2016, implying a barely satisfied status of food security. However, current socio-economic transitioning makes China wealthy to enhance its food security by international trade (Hamshere et al., 2014). If we followed the global waste trajectory, China would actually be a hotspot of global food waste. For example, when China's per capita waste rise up to Japanese level (24 kg cap^{-1} yr^{-1}), USA (124 kg cap^{-1} yr^{-1}), and Canada levels (183 kg cap^{-1} yr^{-1}), a total 32, 168, and 248 Mt will be discarded annually, respectively (Fig. 5a). Referring to the carbon density of 2.6 kgCO_2e kg^{-1}, the embedded carbon footprint would soar up to 82,431, and 637 MtCO_2e yr^{-1}, accounting for 0.7%, 3.7%, and 5.4% of China's total emission in 2013, respectively (11,735 MtCO_2e; WRI, 2013). However, if we followed the estimates of BBN-based waste (Fig. 5b), the likeliest food waste would be 18–25 Mt annually, or 54 Mt in scenario with the average age of family members reaching more than 50 years. It is worth noting that our study was based on CHNS data of 2004, 2006 and 2009 which were available by the time we conducted this study. Although this data may look to be outdated, it is still relevant to investigate the mechanism under household food waste in China since no new data is available. Thus, a better BBN model accuracy would be achieved if newly surveyed data were available.

4. Conclusion

China, which is experiencing rapid urbanization is regarded as a global hotspot of food waste, which trades off its efforts to increase food supply and mitigate climate change. Although revealing the nonlinear mechanism of waste generations is difficult, it is important for future reductions. Based on survey data, this study quantified the food waste of Chinese household and its carbon footprint, and developed a BBN model to predict the possibilities of future waste reductions.

This study show that: (1) Plant-derived food dominates the total waste with a portion of 80–93%, but the animal-derived disproportionally takes up 18–44% of total carbon footprint; (2) The developed BBN model has strong power to predict household food discards, with refrigerator ownership as top factor contributing to waste generations; (3) Household food waste is positively associated with food security status at the global scale; (4) Scenario analysis by China contextualized BBN model doesn't find enough evidence to prove that China will become a global hotspot of food waste.

Among the identified multiple socioeconomic factors in this study, refrigerator ownership play a critical role in reducing household food waste, but consumes power. It worth noting that current ownership rate of refrigerators is 94% in urban China, i.e., approximate 370 million of appliances are running fueled by coal-based electricity and emitting greenhouses gasses both day and night. Thus, an interesting question arise: Can refrigerator pay off carbon debt by lowering food waste? It is worthy for in-depth investigation from a life-cycle perspective.

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Abbreviation

BBN	Bayesian Belief Network
BCFN	The Barilla Center for Food & Nutrition
CF	Carbon Footprint
CHNS	China Health and Nutrition Survey
FAO	Food and Agriculture Organization of the United Nations
GFSI	Global Food Security Index

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jclepro.2018.08.233.

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